Segmentation and localization schemes for non-ideal iris biometric systems

Farmanullah Jan

Department of Physics, COMSATS Institute of Information Technology,

Park Road, Chak Shahzad, 44000, Islamabad, Pakistan

Correspondence: farmanullah_jan@comsats.edu.pk; farmanullahs123@gmail.com.

Abstract: Contemporary surveys focus on the ideal iris biometric systems, which are generally used for overt applications: e.g., border crossing control. Notably, these systems perform well for ideal data, but poorly for non-ideal data. It is because that their iris segmentation modules are generally developed for ideal data, which is acquired under controlled environment using the near infra-red (NIR) illumination only. On other hand, a subject could relatively be *on-the-move* and/or *at-a-distance* from the image acquisition device in non-ideal systems. Non-ideal systems use either the visible wavelength (VW) or NIR illumination while acquiring image data. Non-ideal images may contain noisy factors such as off-axis and off-angle eyeimages, non-circular iris boundaries, and non-uniform illumination. For secure and reliable security measures, non-ideal iris biometric systems are strongly desired around the globe in particular for the covert applications, e.g., monitoring the terrorist's activities. It is observed that literature encompasses research work from the prominent journals in this concern until 2010; therefore, this study includes significant publications following 2010 for both NIR and VW image data. Notably, the main objective of

this survey is to offer a quick-reference regarding recent developments in non-ideal iris biometrics, supplemented with some indispensable prerequisites for beginners and professional researchers.

Keywords: Iris biometric systems, Machine vision, Iris segmentation, Iris localization, Pattern recognition.

1. Introduction

No doubt, recent advances and developments in the field of Information technology (IT) have greatly influenced in our daily routines. For instance, the usage of portable cell phones, global positioning system (GPS), google maps, World Wide Web (WWW), auto teller machines (ATM), autonomous robots, and e-commerce strongly facilitated in our daily life matters. Despite numerous benefits and applications, IT has also brought some unwanted security risks to our valuables, assets, and lives [1-6]. For example, we often hear, read, and/or watch about the cybercrimes, human trafficking, bank frauds, hacking credit cards, illegal access to residential and restricted zones, and among others. Unfortunately, such criminal events often occur because of the weak-chains inherited in the traditional security systems [3, 7].

Today, secure and reliable identification of a person is always a big question: i.e., *is a person really the one who he/she claims to be? Alternatively, who is he/she?* Therefore, to cope with this issue, the biometric technology has rapidly been replacing the traditional security measures. This technology applies the pattern recognition schemes on the physiological (e.g., fingerprint, iris, retina) and/or behavioral (e.g., smell, voice, keystroke) traits of individuals in order to recognize them precisely [7-9]. As it uses a subject's

biometric traits, this technology exempts a person from remembering (e.g., personal identification number (PIN)) or carrying something (e.g., passport) to the identification place. This technology plays an indispensable role in the surveillance and security services [10-12]. It has been functioning successfully in numerous countries, including Germany, Afghanistan, Norway, Canada, Gambia, Australia, India, Iraq, United States, etc. [3]. No doubt, it has great applications in the health and care, citizen registration, forensics and criminal investigation, passport and immigration, border crossing, entrance to residential buildings, e-commerce and e-banking, and so on.

1.1. Why iris biometric?

As stated earlier there are numerous biometric traits, which can be considered while designing a biometric system. However, the overall system's performance greatly relies on how and where it is used. It implies that a designer must thoroughly analyze most of the well-known aspects of a biometric system before developing a biometric system; e.g., the requirements of a system's throughput, task nature (i.e., identification and/or verification), security risks, population size and demographics, interoperability with existing systems, user considerations, and among others. For instance, an iris/face biometric system may perform relatively better than a fingerprint biometric system being deployed at a coalmine. It is because that the fingerprints of workers at coalmine may be worn and/or dirty, which may result in the target system's poor performance. Literature reveals that the performance of a biometric system is prone to resilience of the involved biometric trait [10]. It implies that for system robustness, the concerned biometric trait must possess most of the following characteristics [10, 11, 13]: universality, permanence, collectability, performance, acceptance, singularity, scalability, accuracy, inimitable, and privacy [10].

In recent decades, researchers devised numerous biometric systems based on different

biometric traits such as the palm, retina, fingerprints, signature, and voice [3]. However, these biometric measures are relatively invasive [12], because they require a subject's involvement while acquiring his/hers biometric data such as signing a phrase, touching a sensors-pad, and reciting a pass-phrase. In addition, face is considered relatively a non-invasive biometric trait but it may not stay stable due to the beard, facial surgeries, and aging effects [3, 7, 11]. On other hand, the iris biometric technology recognizes individuals based on their iris texture. Iris is an externally visible internal organ, which is protected by the cornea. It is an annulus sandwiched between the sclera and pupil. Notably, its complex structure (see Fig. 1) comprises the crypts, freckles, corona, furrows, ridges, and arching ligaments. Literature reveals that the iris' structure remains consistent over the whole life of an individual, except some minor changes occurring in the early life stages [12, 13]. Iris is a non-invasive biometric trait, because it does not have any physical contact with the image acquisition device while acquiring image data.

A typical iris biometric system (Fig. 2) comprises four basic modules: *Eyeimage acquisition*, *Iris segmentation*, *Features extraction*, and *Matching and recognition*.

Literature reveals that each of these modules plays an indispensable role in the overall system's performance, but the iris segmentation module plays a very pivotal role. It is because that it demarcates the actual iris inner (Pupillary) and outer (Limbic) boundaries, and detects and marks the superimposed noise in the valid part of iris if any. As stated earlier, the commercial iris biometric systems, based on the pioneered algorithms of Daugman [12] and Wildes [13], perform well for ideal data but poorly for non-ideal data [3, 7]. It is mainly because of their iris segmentation algorithms, which are developed for controlled environment. The ideal image data is acquired in a very constrained environment, e.g., a subject wearing no cosmetics (e.g., eyeglasses) stands at relatively short distance and looks

directly into the image acquisition device. In this concern, the image quality is controlled via an audio and/or visual feedback. On the other hand, images in the non-ideal systems are acquired under relaxed conditions [11, 14]. In such systems, eyeimages are acquired from a subject being on-a-move and/or at-a-distance from the image acquisition device using VW or NIR illumination. Notably, the acquired eyeimages in non-ideal systems may contain multiple noisy factors such as the specular/light reflections, non-uniform illumination, low contrast, blurring, focus, eyeglasses and contact lenses, off-axis and off-angle eyes, eyelashes, eyelids, and hair [3, 7, 11, 15, 16].

1.2. Literature survey highlighting the need of this study

In 2006, Proenca and Alexandre [17] published an article containing the overview of iris segmentation methodologies. It mainly focused on the analysis of the ability of the iris segmentation schemes in order to process eyeimages having heterogeneous characteristics, which simulate the dynamics of a non-cooperative environment. In this concern, authors tested the accuracy of four selected iris segmentation schemes on a VW iris database, i.e., UBIRIS V1.0 iris database, and concluded their performance against the non-ideal issue such as the focus, reflections, brightness, and/or eyelids occlusions. In 2008, Bowyer *et al.* [11] composed a comprehensive survey including the historical development and current state-of-the-art in image understanding for iris biometrics. In this study, authors categorized most of the research publications according to their primary contributions to each of the basic four modules of a typical iris biometric system. Besides, authors provided explicit details regarding the experimental evaluations, iris databases, applications and systems, and the medical conditions affecting the iris' texture as well. Though this survey offers exclusive details, its scope is limited to the work done until 2007 that mainly focuses on ideal iris biometric systems. Besides, Bowyer *et al.* [14] also published another survey to update their

previous work [11]. However, this time, they include the iris biometrics research being published from 2008 to 2010. Following 2010, other iris biometric research articles are also published, but with limited scope. As the area of unconstrained iris biometric systems is still immature, therefore the research work in this area is continued [18].

In 2010, Sheela and Vijaya [19] presented an iris recognition survey. It presented some significant iris recognition methods, benchmark databases, and products. However, its literature survey scope is quite limited. In 2013, Adegoke *et al.* [20] presented a survey on iris segmentation. In this case, authors included some state of the art in iris recognition; but unfortunately, they could not provide basic details necessary for a common reader's understanding. Ironically, the authors even did not offer a single eyeimage throughout the text. In 2013, Abbasi *et al.* [21] claimed to present a critical survey on iris based recognition systems, but they also failed in providing the requisite details. Similarly, in 2013, Manchanda *et al.* [22] published a survey on iris segmentation. However, in this article, authors just described some commonly used boundary localization operators and techniques: e.g., the Integro-differential operator (IDO), Hough transform, Fuzzy clustering algorithm, and among others. This paper does not offer a comprehensive survey of contemporary iris segmentation and localization schemes. In 2012, Rakesh and Khogare [23] published an iris recognition survey, where authors provided only a brief overview of the different feature extraction methods.

To summarize, Bowyer *et al.* [11, 14] provided an exclusive literature survey on the iris biometrics but with its scope confined until 2010. It includes literature for both ideal and non-ideal iris biometric systems. Besides, Proenca and Alexandre [17] presented relatively a good survey on the less-constrained iris biometric systems, but it includes limited publications until 2006. As highlighted above, other researchers also contested on the same topic; but,

unfortunately, they could not provide necessary details required for a survey article. Due to these facts, this study covers all potential papers published following 2010, particularly on the topic of iris segmentation and localization for the non-ideal systems. In addition, this study explicitly details the ideal and non-ideal iris biometrics systems supplement with some basic iris biometric literature, which could surely provide a better platform to the beginners.

The rest of this article is organized as follows. Section 2 explicitly differentiates between the ideal and non-ideal iris biometric systems. Section 3 presents an elaborate survey of state of the art in the iris segmentation and localization schemes for the non-ideal systems. Finally, Section 5 concludes this study.

2. Ideal versus non-ideal iris biometric systems

This section explicitly differentiates between the ideal and non-ideal iris biometric systems.

2.1. Ideal iris biometric systems

This section comprises three essential modules: *Iris recognition technology: a historical perspective*, *Dousman's iris biometric approach*, and *Wildes' iris biometric approach*.

2.1.1. *Iris recognition technology: a historical perspective*

In the history of iris biometrics, Albert Bertillon (a French physicist) first realized the importance of iris for the human recognition in 1880 [12, 13, 15]. Bertillon had practiced using iris as a security trait to identify criminals. Next, Frank Burch (an ophthalmologist) suggested the application of iris as a biometric measure for human recognition in 1936. Following that, Flom and Safir in 1985 suggested that no two irises are alike [24]. For this effort, they were awarded with a patent (patent # 4,641,349) in 1987 [25, 26]. Although this patent inherits a conceptual theoretical scheme of an automated iris biometric system with

controlled conditions, it contains some useful recommendations that strengthened the later iris biometric research. Then, Safir and Flom consulted John Daugman in order to develop a working algorithm for their proposed scheme in 1989 [25]. Meanwhile, the Defense Nuclear Agency (DNA) had also started developing a workable prototype for iris biometric system, which was completed by Safir, Flom, and Daugman in 1993. This achievement resulted in a patent (U.S. Patent No. 5,291,560) in 1994 as an award to John Daugman [18]. Following that, Wildes *et al.* [27] patented (Patent number: 5572596) a new iris biometric system in 1996. Similarly, Matsushita also patented (Patent number: 5901238) a new iris biometric system in 1999 [15]. During this era, other iris biometric algorithms were also published and patented [27].

Notably, Flom, Safir, and Daugman then established a company: "Iridian Technologies, Inc.", and they assigned the patent # 4,641,349 to it [15]. Surprisingly, this patent did not allow other companies to do business in the iris biometric market for approximately 20 years, which is mainly because of its broader scope. This patent says '*Maybe the iris can be used like a fingerprint*'. *If anyone can figure out a way to do it, we own it*' [18]. The Flom/Safir's first patent and other worldwide patents then expired in 2005 and 2007, respectively [26]. However, during that deadlock, numerous new iris recognition techniques were also patented, some of them were even more superior to Daugman's algorithm [11, 16]. Finally, other two of Daugman's patents (i.e., EP0664037A1, and WO09409446) also expired on 15th July 2011 and 10th October 2012, respectively [18]. Today, the research community is actively involved in developing new iris recognition schemes, in particular for the non-ideal iris biometric systems.

2.1.2. *Daugman iris biometric approach*

Daugman's iris recognition algorithm [12, 13] includes four functional modules:

Eyeimage acquisition, Iris segmentation, Features extraction, and Matching and recognition.

a) Eyeimage acquisition: It acquires eyeimages from a subject through a controlled image acquisition setup (see Fig. 3(a)) [11, 12]. In this case, a subject wearing no contact lenses and/or eyeglasses stands still at a short distance and gazes directly into the camera's view. Herein, the image quality is controlled in real-time by analyzing the total high frequency power in its 2D Fourier spectrum. The image acquisition setup maximizes this spectral power by either tuning the camera's focus or guiding the concerned subject with a visual/audio feedback. Eyeimages are acquired using NIR illumination (700:900nm) [12]. Most importantly, NIR illumination is equally useful for both the light and dark irises [3, 7, 11]. However, for optimal performance, iris diameter in the resultant eyeimage is recommended to be at least in the following range: (140:200) pixels [3, 7, 11]. Lastly, the deformable templates are utilized to extract the eye-part from the acquired face image [11, 12]. Such templates are often adapted in the machine vision applications to extract various facial features, e.g., eye location, eyelids [11, 16]. Fig. 3(b) illustrates a typical application of the ideal iris biometric system [11, 16]. Besides, Fig. 3(c) & (d) shows some typical NIR eyeimages acquired under ideal conditions [28, 29].

b) Iris segmentation: This module segments iris from an eyeimage, assuming its inner and outer boundaries as two non-concentric circles. To do so, Daugman [11, 30] devised a useful edge-detecting operator, which is known as the Integro-differential operator (IDO). It is defined as

$$\max_{(r, x_o, y_o)} \left| G_\sigma(r) * \frac{\delta}{\delta r} \oint_{r, x_o, y_o} \frac{I(x, y)}{2\pi r} ds \right|, \quad (1)$$

where $G_\sigma(r)$ is a smoothing function (e.g., the Gaussian-filter with scale σ) and $*$ represents the convolution operation. Notably, IDO searches over the entire image domain

(x, y) to find a maximum in the blurred partial derivative, with respect to increasing the radius r , of the normalized contour integral of the input eyeimage $I(x, y)$, along a circular arc ds centered at (x_o, y_o, r) . Where (x_o, y_o) and r indicate the center and radius of circular arc, respectively.

To localize iris contours, Daugman first applied IDO on $I(x, y)$ to localize the coarse limbic boundary. While localizing limbic boundary, he biased IDO for the horizontal direction only. Notably, this biasing is adapted in order to escape eyelids occluding iris in the vertical direction. Then, he reused IDO to localize pupillary boundary within a small region centered at the coarse iris center. While localizing pupillary boundary, he also biased IDO for the upper 270° cone to avoid the corneal reflections, which are generally superimposed in the lower 90° iris cone by an illuminator located below the video camera. Following that, he reused IDO to localize the fine limbic contour in a local region centered at the pupil center. Finally, Daugman localized eyelids in the localized iris by using a line version of IDO [11, 13].

c) *Features extraction*: Literature reveals that the iris' geometry in different eyeimages acquired from the same individual's eye may not necessarily be alike. It is mainly because of the different image acquisition setups, distances between the subject's eye and camera, pupil dilation, and among others [15]. To resolve this issue, Daugman come up with a very flexible solution: a *rubber sheet model*, which transforms an annular iris region $i(x, y)$ into a rectangular strip (see Fig. 4). This model transforms each point (x, y) in $i(x, y)$ to a pair of the polar coordinates (r, θ) , where $r \in [0 \ 1]$ and $\theta \in [0 \ 2\pi]$. This transformation is carried out as

$$i(x(r, \theta), y(r, \theta)) \rightarrow p(\bar{r}, \bar{\theta}), \quad (2)$$

with $x(r, \theta) = (1-r)x_p(\theta) + rx_i(\theta)$; $y(r, \theta) = (1-r)y_p(\theta) + ry_i(\theta)$ and,

$$x_p(\theta) = x_{po} + r_p \cos \theta; \text{ and } y_p(\theta) = y_{po} + r_p \sin \theta; x_i(\theta) = x_{io} + r_i \cos \theta; y_i(\theta) = y_{io} + r_i \sin \theta.$$

Where (x, y) represents the original Cartesian-coordinates; (r, θ) corresponding normalized polar coordinates; (x_p, y_p) and (x_i, y_i) coordinates of the pupillary and limbic boundaries along θ direction, respectively; and (x_{po}, y_{po}) and (x_{io}, y_{io}) the center coordinates of pupil and iris regions, respectively. It is evident from Fig. 4 that the normalized iris contains noise (i.e., eyelid occlusions), which are then detected and marked in the subsequent noise-mask accompanying the iris template. The rubber sheet model considers $i(x, y)$ as a flexible rubber-sheet anchored at iris boundary, with pupil center as a reference point. Due to this flexible transformation, most of the iris inconsistencies are rectified except the rotational issue that is compensated through a shifting operation during the matching process.

Now to extract texture features from $p(\bar{r}, \bar{\theta})$, Daugman used the following 2D Gabor wavelet filters [1, 2, 4, 11, 16] as

$$G(x, y) = e^{-\pi[(x-x_o)^2/\alpha^2 + (y-y_o)^2/\beta^2]} e^{-2\pi i[u_o(x-x_o) + v_o(y-y_o)]}, \quad (3)$$

where (x_o, y_o) specifies the pixel position in the target image; α and β specify the effective width and length, respectively; and (u_o, v_o) specifies modulation having spatial frequency $w_o = \sqrt{u_o^2 + v_o^2}$. Here, compression was achieved by demodulating the filters' outputs. The resultant encoded iris texture is represented as a binary code (called IrisCode, see Fig. 5(a)).

d) Matching and recognition: After obtaining IrisCode, Daugman applied the normalized Hamming distance (*HD*) as a decision metric. It is defined as

$$HD = \left(\frac{1}{n} \right) \sum_{j=1}^n (X_j \otimes Y_j). \quad (4)$$

Where, X and Y represent the binary strings of a target (probe) and the stored (gallery) IrisCodes in the concerned database, respectively; n is length of each string, and $\otimes$ an XOR logical operation. Here, the zero value of HD means a perfect match between X and Y , but its higher value means that IrisCodes do not belong to same individual. For practical applications, the system's designer will experimentally set a threshold-value for HD . For instance, Daugman achieved optimal accuracy results over 2.3 million comparison between different irises, for $HD = 0.33$ [12, 31]. Notably, for optimal system performance, only noise-free pixels of X and Y are matched with each other. Therefore, a *noise-mask* (see Fig. 5(b)) indicating the positions of noise-free pixels in its respective IrisCode (see Fig. 5(a)) is also developed while extracting features. Fig. 5(a) & (b) illustrates an IrisCode and its noise mask, respectively, which are generated from the normalized iris shown in Fig. 4.

2.1.3. Wildes iris biometric approach

Wildes [13, 27] patented a new iris biometric system in 1996. It is considered as a first parallel of the Daugman's approach [12]. Wildes designed a functional iris biometric system at the Sarnoff Labs in 1997, but with different structure from Daugman's system [12]. For this design, he devised a new image acquisition setup comprising the circular polarizers, diffusers, a camera, and among others (see Fig. 6). The main benefit of this design is that it does not cause any specular reflections in acquired eyeimages [13]. Likewise Daugman's system, it uses NIR illumination to acquire image data and imposes almost similar restrictions on a subject as Daugman's system does.

To segment iris, Wildes utilized a combination of the edgemap of the input eyeimage $I(x, y)$ and the Hough transform to localize the iris inner and outer contours and eyelids if

any. To start with, Wildes first extracts an edgemap $E(x, y)$ from $I(x, y)$ by thresholding the magnitude of intensity gradients in $I(x, y)$. The magnitude of that intensity gradient is defined as

$$|\nabla G(x, y) * I(x, y)|, \quad (5)$$

where $G(x, y)$ represents the 2D Gaussian filter centered at (x_o, y_o) , with standard deviation σ . It is used to calm down the sharp gray-level intensities in $I(x, y)$, which generally results in blurring. Similarly, ∇ represents a Two-dimensional (2D) gradient-operator defined as $\nabla \equiv (\delta/\delta x, \delta/\delta y)$. Likewise the IDO, Wildes also biased ∇ in some specific directions while computing the edgemap $E(x, y)$ from $I(x, y)$. Notably, this biasing is generally preferred when the system's optimal performance is desired. Assuming the subject's head upright, Wildes biased it in the vertical and horizontal directions while localizing the limbic boundary and eyelids, respectively. Fig. 7(b)-(d) illustrates $E(x, y)$ extracted from $I(x, y)$ given in Fig. 7(a) by biasing ∇ in the vertical and horizontal, vertical, and horizontal directions, respectively.

Next Wildes used circular Hough transform (CHT) to localize the pupillary and limbic boundaries, assuming them as two non-concentric circles. Literature reveals that Hough transform is most often used in machine vision applications to detect two-dimensional (2D) objects, e.g., line, parabola, circle, and ellipse [3, 7, 11, 16]. As it is tolerant to the broken contours of objects in a binary image, therefore it is tolerant to the noisy artifacts as well [3, 7]. For a circle centered at (x_c, y_c) and having radius (r_c) , its CHT accumulator (H_c) is defined as

$$H_c(x_c, y_c, r_c) = \sum_{k=1}^n H(x_k, y_k, x_c, y_c, r_c), \quad (6)$$

where n is the total number of edge-pixels in $E(x, y)$ and:

$$H(x_k, y_k, x_c, y_c, r_c) = \begin{cases} 1, & \text{if } h_t(x_k, y_k, x_c, y_c, r_c) = 0 \\ 0, & \text{otherwise.} \end{cases}$$

With $h_t(x_k, y_k, x_c, y_c, r_c) = (x_k - x_c)^2 + (y_k - y_c)^2 - r_c^2$. For each edge-pixel (x_k, y_k) in $E(x, y)$, for $k = 1, 2, 3, \dots, n$, votes are cast in H_c for a circle radii-range $(r_1 : r_2)$. Where r_1 and r_2 denote the lower and upper radii-range of (x_c, y_c, r_c) , respectively [32]. If an edge-pixel lies on (x_c, y_c, r_c) in $E(x, y)$, then the value of $h_t(x_k, y_k, x_c, y_c, r_c)$ equals to one else zero. Finally, a location (x_c, y_c, r_c) for which H_c becomes maximum is taken as the *parameter vector* of the target circle. Fig. 8(a) illustrates a 2D view of H_c for a specific radius. Similarly, Wildes localized eyelids in iris using the parabolic Hough transform (PHT). Fig. 8(b) depicts an iris localized via this approach.

To extract features, Wildes applied the Laplacian of Gaussian (LOG) filters oriented at multiple scales in order to yield the template. Note, here the filtering results are not binarized to get a compact template as done in the Daugman's approach. Finally, Wildes suggested the use of *normalized correlation* as the decision metric for matching. Wildes' approach has demonstrated very promising results. For example, it demonstrated zero False Accept Rate (FAR) and zero False Reject Rate (FRR) for an iris database of 600 eyeimages collected from 60 individuals [15].

2.2. Non-ideal iris biometric systems

For Daugman's type iris biometric systems [12, 23], both ideal and non-ideal biometric systems are comprised of the same aforementioned basic four modules. However, these

systems differ only in the first two modules: i.e., image acquisition and iris segmentation [11, 15, 33]. As stated earlier, the image quality in ideal systems is monitored by constraining an individual. However, in non-ideal systems, the subject could be relatively relaxed, due to which the image quality may not be ideal. In context with the level of imposed constraints, the non-ideal iris biometric systems can be categorized into two basic classes [15]: i) *Less-constrained iris biometric systems* and ii) *Un-constrained iris biometric systems*.

2.2.1. *Less-constrained iris biometric systems*

In literature, there exists no thumb-rule that can be used to differentiate between the less-constrained and un-constrained iris biometric systems [3]. Nevertheless, a subject in the less-constrained environment always stays under some minimum restrictions but relatively relaxed compared with ideal environment [15]. These systems can use either NIR or VW illumination while acquiring image data. Herein, an individual can wear cosmetics (e.g., eyeglasses, artificial eyelashes) [11, 32, 34] and, to some extent, he/she could also be on the move but with slow pace, and/or at a distance as well. In this case, the acquired eyeimages may contain several noisy issues such as the non-uniform illumination, low contrast, rotated-iris images, off-angle and off-axis eyeimages, non-circular iris boundaries, and among others [3, 15, 16, 18]. As the level of constraints for such systems is not fixed, therefore these systems can be equipped with the image acquisition setup either of the ideal systems or the one as illustrated in Fig. 9 [11, 14, 17, 35].

2.2.2. *Un-constrained iris biometric systems*

Ideally, a subject in the un-constrained environment should be under zero-constraints. It means that such systems should be tolerant to the large distances, moving pace, and/or cosmetic stuff (e.g., eyeglasses) of an individual. Notably, such features are strongly required

for the covert applications, where an individual is even unaware about the system's deployment; e.g., monitoring criminal activities at public and private places [15, 18]. Unfortunately, such zero-constraints iris biometric systems are not matured yet [18] and, therefore, demand for more struggle from the concerned research community [15, 18, 36]. These systems can also use either VW or NIR illumination in order to acquire image data. In these systems, the acquired images may also contain similar noisy factors just mentioned. Fig. 10 (a) & (b) illustrates some sample eyeimages acquired with NIR and VW illumination, respectively. Notably, such eyeimages are commonly found in non-ideal systems [15, 35].

3. Non-ideal iris segmentation and localization schemes: *a survey following 2010*

As stated earlier, iris segmentation plays an indispensable role in the overall system's performance. It is because that it isolates the valid iris part, which is then fed to the systems' subsequent modules. It means that an inaccurately localized iris will surely degrade the system's performance [11, 14]. Based on this argument, state-of-the-art iris literature [11, 14, 15] is mainly focused on the topic of iris segmentation and localization. As stated earlier, the commercial iris biometric systems perform poorly for non-ideal data. It is mainly because of their iris segmentation and localizations schemes that are developed for the controlled data only [3, 7]. To resolve this issue, researchers contributed significant work in this area. However, this issue is still immature and demands for more efforts from researchers around the globe [18]. In this concern, researchers devised numerous iris segmentation and localization algorithms based on various techniques, e.g., the gradients and edge descriptors [15], active contours models [37-40], genetic algorithms and neural networks; and histogram and thresholding [11, 14], and among others. Notably, this study highlights important contemporary iris segmentation and localization schemes published following 2010, in particular for non-ideal environment. In this study, the following aspects of iris segmentation

and/or localization schemes are considered:

- i) *Specular/light reflections,*
- ii) *Iris contours localization, and*
- iii) *Noise detection and removal.*

In 2011, Chen *et al.* [41] published: *Iris segmentation for non-cooperative recognition systems*. In this study, authors focused on localizing iris in the presence of noise such as the lighting variations, subject on-the-move, and off-angle view eyeimages. In this case, authors first devised an adaptive mean shift scheme for estimating the rough iris center. Next, they set a circle as an initial iris outer contour. After combining the statistical texture prior modeled as Markov random field, a merged active contour model (MAC) is established in terms of the level-set theory. The MAC model iteratively drives the initial contour to the real iris boundaries. Notably, the noisy regions (e.g., eyelids, eyelashes, reflections, and shadows) are also avoided in the valid iris regions during the curve evolving process. In terms of recognition accuracy, this scheme achieved $EER = 0.43$, for a set of 3,500 eyeimages randomly selected from the THUIris V1.0 [41], CASIA-IrisV3-Lamp [28], and ICE V1.0 [11, 16] iris databases. Where, EER stands for the equal error rate. It is the point where the false accept rate (FAR) and false reject rate (FRR) becomes equal [11]. As indicated in Table 1, on the average (*MATLAB V7.0, CPU: Intel Pentium IV, CPU speed: 2.0 GHz; 1GB RAM*), it takes 38 milliseconds (ms) to segment an iris in the input eyeimage. Fig. 11 illustrates some segmentation results of this scheme on the stated iris database.

In 2011, R.M. Farouk [42] published: *Iris recognition based on elastic graph matching and Gabor wavelets*. First, authors use CHT to localize the iris outer boundary. Next, they mark a set of points around iris center as the pupil initialization. After that, they localize the iris inner boundary using the region-based active contours. Following that, they detect eyelids

by first fitting a line to the upper and lower eyelids using the linear Hough transform (LHT). Next, they draw a horizontal line intersecting with the first line at the iris edge being closest to pupil. Lastly, they draw a second horizontal line allowing the maximum eyelids isolation. This scheme is tested on the UBIRIS V1.0 [43] (34 images excluded) and CAISA-IrisV3-Interval [28] (81 images excluded) iris databases, which resulted in 97.17% and 95.8% recognition accuracy, respectively (Table 1). Fig. 12 illustrates segmentation results of this method on the stated iris databases.

In 2011, Roy *et al.* [44] published: *Iris recognition using shape-guided approach and game theory*. To begin with, authors first suppress specular reflections in the pupil region as follows. First, they complement input eyeimage, fill holes in pupil region, and smooth down sharp gray-level variations in resultant image using the Gaussian filter. Next, they estimate pupillary boundary using the Direct Least Square (DLS) based elliptical fitting scheme. After that, they localize iris outer boundary using a geometric shape prior with local and global information. As iris outer boundary is localized using the active contours model, therefore eyelids and eyelashes' occlusions are also escaped from the valid iris part. A similar approach is also given in [45]; in this article, authors first demarcate the iris inner and outer contours via the DLS-based elliptical fitting. Finally, based on the approximation of iris inner and outer contours, a curve is evolved using the level-set supplemented with a variational formulation technique for accurate segmentation of pupil and iris regions. This scheme [45] is tested on the same databases. The scheme given in [44] is tested on the ICE 2005 [46], CASIA-IrisV3-Interval [28], UBIRIS V1.0 [43], and WVU V1.0 [47] iris databases, which resulted in the following correct recognition rate (CRR): 98.30%, 97.21%, 97.49%, and 95.68%, respectively (Table 1). On the average (*MATLAB V7.2, CPU: Pentium IV, CPU speed: 3.0 GHz; 2.5GB RAM*), it takes 804ms for iris segmentation in the input eyeimage. Fig. 13 illustrates

some segmentation results of this scheme.

In 2011, Roy *et al.* [48] published: *Towards nonideal iris recognition based on level set method, genetic algorithms and adaptive asymmetrical SVMs*. First, authors demarcate the iris inner and outer contours via the DLS-based elliptical fitting scheme. Next, they apply a level set based curve evolution approach using the edge stopping function to demarcate the iris inner boundary. Then, they detect iris outer boundary through the curve evolution approach using the regularized Mumford–Shah segmentation model, with an energy minimization algorithm. As iris outer boundary is localized via the active contours model, therefore eyelids and eyelashes are also escaped from the valid iris part. This scheme is tested on the ICE 2005, WVU V1.0 [47], and UBIRIS V2.0 [43] iris databases, which resulted in the following recognition accuracy: 98.21%, 96.32%, and 97.51%, respectively. As briefed in Table 1, on the average (*MATLAB V7.2, CPU: Pentium IV, CPU speed: 3.0 GHz; 2.5GB RAM*), it takes 810ms for iris segmentation in the input eyeimage. Fig. 14 illustrates some segmentation results of this method.

In 2011, Yingzi *et al.* [49] published: *Video-Based Noncooperative Iris Image Segmentation*. In this scheme, a remote iris acquisition system is adapted to acquire non-cooperative iris video images from the subjects. Authors use a quality filter to exclude images containing no subject's eye. Next, authors use a DLS-based elliptical fitting scheme to demarcate pupil and limbic boundaries. After that, they develop a window gradient-based method to remove noise (i.e., eyelids and eyelashes) in the valid iris part. For computing accuracy results, authors used an objective metric to evaluate segmentation accuracy quantitatively. This scheme is tested on the IUPUI remote iris database [50]. On the average, it achieved 90.08% segmentation accuracy, with standard deviation 6.52% (see Table 1). Besides, recognition accuracy of this algorithm is also computed. With 2D and 1-D log Gabor

filters, this scheme achieved $EER = 0.0179$ and $EER = 0.0295$, respectively. Fig. 15 illustrates some segmentation results of this scheme, for the stated iris database.

Puhan *et al.* [51] in 2011 published: *Efficient segmentation technique for noisy frontal view iris images using Fourier spectral density*. In this article, authors first compute the Fourier spectral density of each pixel based on its neighbors in order to develop a spectral image. Next, they binarize the resultant image via a row-wise adaptive threshold scheme, which is based on the Fourier spectral density. The resultant binary image contains an approximate iris location. Then, they detect and delete objects having areas less than a specific threshold value in the binary image. Following that, they demarcate the partial limbic boundary by computing an array containing the lengths of zeros (sandwiched between two white pixels) in each row of binary image. After that, they extract binary image containing coarse iris edges through a hybrid of the thresholding and gradient based technique. Finally, authors extract the radius and center's parameters of circular limbic boundary through a technique based on the Euclidean distances. In addition, they apply a similar approach while localizing circular pupillary boundary. Finally, they localize eyelids via a line approximation. This scheme is tested on both sessions of UBIRIS V1.0 [43], excluding some bad images. On the Session-I and Session-II, it achieved 98.49% and 98.75% segmentation accuracy for limbic boundary; and 94.47% and 87.17% for pupillary boundary, respectively. On the average (*MATLAB, CPU: Pentium IV, CPU speed: 2.66 GHz; 2.0GB RAM*), it takes 15ms for iris segmentation (Table 1). Fig. 16 illustrates some false and accurate iris localization results of this algorithm on the stated iris databases.

In 2012, Radman *et al.* [52] published: *Iris Segmentation in Visible Wavelength Environment*. First, authors localize a coarse pupil center using a circular Gabor filter. Next, they localize iris outer boundary within a small window using the modified edge-detecting

operators, i.e., IDO and CHT. Then, they localize iris inner boundary by reusing these operators in a small window located around the iris' center. Then, authors present a scheme to detect and remove noise. Instead of its temporal results, authors presented the computational complexity for this scheme as

$$(17*17*R_i)+(11*11*R_p)+12*(N*M), \quad (7)$$

where N and M represent the length and width of concerned image, respectively; and R_i and R_p indicate the radii-ranges for iris outer and inner circular boundaries, respectively. This algorithm is tested on both sessions of UBIRIS V1.0 [43]. For the modified IDO, it demonstrated 99.67% and 99.35% recognition accuracy on the Session-I and Session-II, respectively. Similarly, for the modified CHT, it achieved 99.42% and 98.53% recognition accuracy on Session-I and Session-II, respectively (Table 2). Fig. 17 illustrates some segmentation results of this scheme.

In 2012, Jan *et al.* [3] published: *Iris localization in frontal eye images for less constrained iris recognition systems*. In this article, authors first preprocess the input eyeimage through an effective adaptive-based preprocessing scheme. This scheme effectively replaces the gray-level intensity of specular reflections in input eyeimage with a lower gray-level value and calms down the sharp gray-level intensity variations if any. Next, they localize the circular iris inner and outer contours in resultant image using an iterative-based two-pass technique. In the first-pass, they use a hybrid of CHT, adaptive thresholding, image gray-level statistics, and a geometrical transform to demarcate circular iris inner contour in a sub-image containing coarse pupil region. After that, they localize circular iris outer contour in another sub-image centered at pupil's center. Notably, if first-pass is failed, then its second-pass invokes to localize a sub-image containing coarse iris region. Next, it localizes

circular iris inner contour within sub-image by reutilizing the same procedure as adapted for first-pass. Then, it localizes circular iris outer contour. Notably, in either case, authors validate the pupil location through an effective occlusion transform. Finally, they also regularize iris contours via a hybrid of the Fourier series and radial gradients. Accuracy of this scheme is computed subjectively, i.e., manually. The following experimental setup: MATLAB V7.1, CPU: Pentium IV, CPU speed: 2.33 GHz; and 1.0GB RAM is involved in validating this algorithm. As indicated in Table 2, on the average, it takes 2.67, 2.70, 7.20, 7.75, 3.91, 6.40, 4.93, 5.61, 1.14, and 8.52 Seconds (Sec) to localize iris in the input eyeimages taken from the MMU V1.0 [29], MMU (new) V2.0 [29], CASIA-IrisV1 [28], CASIA-IrisV3-Interval [28], CASIA-IrisV3-Twins [28], CASIA-IrisV3-Lamp [28], CASIA-IrisV3-Thousand [28], CASIA-IrisV4-Syn [28], UBIRIS V1.0 [28], and IITD V1.0 [53], respectively. Similarly, this scheme achieved 100%, 99.90%, 100%, 99.5%, 97%, 98%, 99.5%, 100, and 93.5% accuracy results, respectively, on the stated iris databases. Fig. 18 illustrates some false and accurate iris localization results of this scheme.

In 2012, Mahlouji and Noruzi [54] published: *Human Iris Segmentation for Iris Recognition in Unconstrained Environments*. In this article, first authors preprocess the input eyeimage as follows. Authors use the Canny edge detector to enhance the iris outer contour, use a multiplier function to enhance the Canny iris points, and adjust the image contrast in order to make its pixels relatively more brighter. After that, they use CHT and LHT to localize the iris inner/outer contours and eyelids, respectively. As indicated in Table 2, on the CASIA-IrisV1 [28], CASIA-IrisV3-Interval [28], and BATH V1.0 [55], this scheme achieved 98.13%, 99.73%, and 99.18% localization accuracy for pupillary boundary and 99%, 99.19%, and 99.70% for limbic boundary; and 98%, 98.63%, and 97.63% for eyelids, respectively. Fig. 19 illustrates some segmentation results of this scheme.

In 2012, Mehrotra *et al.* [56] published: *Fast segmentation and adaptive SURF descriptor for iris recognition*. This scheme works as follows. First, authors binarize input eyeimage via a series of threshold-values, record the count of binary objects in each case, and select only that value as an adaptive-threshold for which the lowest objects count exists. However, in case, if more than one-threshold values correspond to same objects count, then the maximum threshold-value is taken as an adaptive-threshold. Next, they binarize input eyeimage using this threshold, complement resultant image, fill holes, and compute a spectrum image. Then, a pixel having highest gray-level intensity in spectrum image is considered as pupil center. To compute pupil radius, authors compute an edgemap of binary image (with holes filled), and then count the number of pixels between the central and a nearest non-zero pixel. Similarly, to localize limbic boundary; authors first blur input eyeimage, enhance its contrast, draw a band of circles centered at pupil center, and; lastly, only that circle is considered as fine limbic boundary for which the sum of gray-level values computed on its perimeter is maximum with respect to its previous circle. In this article, authors do not propose any strategy for detecting and removing noise in localized iris. As indicated in Table 2, on BATH V1.0 [55], CASIA-IrisV3-Interval [28], and UBIRIS V1.0 [43], this scheme achieved 99.02%, 99.55%, and 96.59% localization accuracy, respectively; similarly, on the average (AMD Athlon dual core 2.81 GHz processor and 2 GB RAM), it takes 0.3383, 0.3960, and 0.2820 Sec for iris localization, respectively. Fig. 20 illustrates some segmentation results of this method.

In 2013, Jan *et al.* [7] published: *Reliable iris localization using Hough transform, histogram-bisection, and eccentricity*. To preprocess input eyeimage, authors first complement input eyeimage, detect holes using the 4-connectivity procedure, fill holes using bi-linear interpolation, re-complement resultant image, and then pass it through a median filter to calm down the spiky noise and resultant artifacts if any. Next, they localize coarse iris

location in input eyeimage using a hybrid of CHT and the image gray-level statistics. After that, they localize pupillary boundary using a bi-valued adaptive-threshold and 2D object shape properties. Following that, they localize limbic boundary by reusing a hybrid of CHT and image statistics. Finally, they regularize iris boundaries using a combination of the Fourier series and radial gradients. Accuracy of this scheme is also computed subjectively. It is validated on CASIA-IrisV1 [28], CASIA-IrisV3-Lamp [28], CASIA-IrisV4-Thousand [28], IITD V1.0 [53], MMU V1.0 [29], and MMU (new) V2.0 [29], which resulted in 100%, 99.21%, 99.23%, 99.23%, 100%, and 99.12% accuracy results, respectively. Similarly, on the average (*Matlab V7.1, Intel Pentium-V with clock speed 2.33 GHz, and 1 GB RAM*), it takes 3.0, 3.35, 3.4, 3.6 1.2, and 1.4Sec, respectively (Table 3). Fig. 21 illustrates some false and accurate iris localization results of this scheme on the stated iris databases.

In 2013, Sahmoud and Abuhaiba [57] published: *Efficient iris segmentation method in unconstrained environments*. In this article, authors proposed an algorithm to effectively segment iris in VW eyeimages. First, authors determine the expected region of iris via the K-means clustering algorithm. Next, they use CHT to extract the iris radius and center. Following that, authors localize the upper eyelids through an effective scheme. In addition, they localize the lower eyelids with LHT. Reflections are also removed, in the RGB domain. To localize pupil, they enhance iris image by mapping its bits' intensity values to new values in order to focus on the dark pixel values, and then apply CHT to demarcate pupillary boundary. As indicated in Table 3, this scheme achieved 98.76% segmentation accuracy on UBIRIS V1.0 [43]. On the average (*MATLAB V7.0, Core 2 Due Intel Pentium IV, and 2 GB RAM*), this scheme takes 1.49Sec. Fig. 22 illustrates some accurate iris segmentation results of this algorithm.

In 2013, Jan *et al.* [2] published: *Robust iris biometric system for visible wavelength data*.

In this article, authors first suppress specular reflections and sharp gray-level intensity variations in the input eyeimage through a median filter. After binarizing resultant image via the Otsu's thresholding method and subsequently filling holes via the bilinear interpolation scheme, authors next compute the Euclidean distance transform (EDT) of resultant image. Following that, a pixel having maximum value in EDT image is taken as the seed-pixel. Then, authors use a hybrid of the circular-pixel counting scheme (CPCS) and a region of interest centered on the seed-pixel to localize the iris outer boundary. In a similar fashion, the iris inner boundary is marked within iris. Next, they localize eyelids in the polar form of localized iris part using the Parabolic-pixel counting scheme (PPCS). Similarly, they detect reflections, eyelashes, and skin parts through an adaptive scheme based on the image gray level intensity in the iris polar form. As indicated in Table 3, on UBIRIS V1.0 [43] and CASIA-IrisV3-Interval [28], this scheme achieved 99.6% and 99.4% recognition accuracy, respectively. Similarly, on the average (*MATLAB V7.0, CORETM i5, CPU speed: 2.4GHz, and 2GB RAM*), it takes 0.8Sec and 0.5Sec to generate the IrisCode and Noise-mask, respectively. Fig. 23(a) shows some accurate iris localization results. Similarly, Fig. 23(b) & (c) represents a polar iris image and its corresponding noise mask where eyelids, reflections, and eyelashes are marked, respectively.

In 2013, Radman *et al.* [58] published: *Fast and reliable iris segmentation algorithm*. To suppress reflections, authors complement input eyeimage, fill holes in resultant image, and re-complement it. After that, they utilize the circular Gabor filter to find the rough center position of pupil. Then, they localize iris inner and outer contours via the fast IDO, assuming that the real centers of iris and pupil lie close to each other in small area located around the rough pupil's center. Lastly, they demarcate the upper and lower eyelids using the live-wire technique. This scheme is validated on both sessions of UBIRIS V1.0 [43]. As indicated in

Table 3, this scheme achieved 97.36% and 96.88% segmentation accuracy on Session I and Session II, respectively. On the average (*MATLAB, 2.4 GHZ Dual core PC, and 2 GB RAM*), it takes 1.09Sec for iris segmentation. Fig. 24 illustrates some accurate segmentation results of this scheme.

In 2013, Jan *et al.* [59] published: *Iris localization based on the Hough transform, a Radial-gradient operator, and the gray-level intensity*. To preprocess input eyeimage, authors first complement input eyeimage, detect holes using 4-connectivity scheme, fill holes using bi-linear interpolation, re-complement resultant image, and pass it through a median filter in order to smooth down spiky noise and the effects of artifacts if any. Next, authors localize a small region containing coarse iris location using a combination of the CHT and image gray-level statistics. Following that, they extract circular pupillary boundary within a small region using an iterative-scheme based on adaptive binarization and use a verification test to validate pupil location. After that, they demarcate circular limbic boundary via CHT. In addition, they validate the actual iris location through an intensity test. Finally, they regularize the iris boundaries through an enhanced method comprising an error-transform (ET), a Radial-gradient operator (RGO), and the Fourier series. This scheme is validated on MMU V1.0 [29], MMU (new) V2.0 [29], CASIA-IrisV3-Interval [28], CASIA-IrisV3-Lamp [28], and CASIA-IrisV4-Thousand [28], which resulted in 100%, 99.2%, 99.4%, 99.25%, and 99.3% localization accuracy, respectively. Similarly, on the average (*MATLAB V7.2, CORETM i5, CPU speed: 2.4GHz, and 2GB RAM*), it takes 0.60, 0.80, 1.23, 1.33, and 1.42 Sec, respectively (Table 3). Fig. 25 illustrates some false and accurate iris localization results of this scheme on the stated iris databases.

In 2014, Saad *et al.* [60] published: *Accurate and fast pupil localization using contrast stretching, seed filling and circular geometrical constraints*. In this article, authors first

enhance the contrast of input eyeimage. Next, they apply the local integration on resultant image to enhance the contrast between the existing white and black areas in resultant image. Notably, this act is useful to compute an optimal threshold value, which is required to perform a successful image binarization for isolating the actual pupil region. After that, they use the seed-fill algorithm as a region growing method to segment binary image and mark pupil as a circular black segment with biggest area. Following that, the approximate pupil center is detected. Next, pupil is filled with black color using a simple filling method in order to remove reflection. Finally, they use a circle fitting strategy to precisely localize circular pupil region. This strategy is based on a fact that the richer iris textures are not closer to pupil boundary. This scheme is validated on CASIA-IrisV3-interval [28], which resulted in 100% pupil localization results (Table 4). Fig. 26 illustrates some false and accurate pupil localization results of this scheme.

In 2014, Jan *et al.* [1] published: *A dynamic non-circular iris localization technique for non-ideal data*. First, authors use an effective scheme based on a multi-valued adaptive threshold and the 2D binary object properties to extract iris inner boundary within a sliding-window in the input eyeimage. Next, they localize iris outer boundary using an edge-detecting operator (i.e., IDO) in a sub image centered at the pupil's center. Finally, they use a combination of Fourier series and radial gradients to regularize the iris' contours. As given in Table 4, this scheme is validated on the CASA-IrisV1 [28], CASIA-IrisV3-Lamp [28], IITD V1.0 [53], and MMU V1.0 [29], which resulted in 100%, 99.05%, 99.46%, and 99.55% localization results, respectively. On the average (*MATLAB V7.1, CORETM i5, CPU speed: 2.33GHz and 2GB RAM*), it takes 1.5Sec for iris localization in an eyeimage. Fig. 27 illustrates some false and accurate iris localization results of this scheme on the stated iris databases.

In 2014, Raffei *et al.* [61] published: *Fusing the line intensity profile and support vector*

machine for removing reflections in frontal RGB color eye images. This article focused mainly on removing light reflections in VW eyeimages. In this case, authors first proposed a combined LIPSVM method based on a line intensity profile to identify reflections. A pixel is considered as a reflection point when its intensity in the red-component of RGB eyeimage is higher than its green and blue counterparts. For this purpose, authors applied the support vector machine (SVM) in order to classify reflections and non-reflections. However, they segmented iris as follows. First, they use CHT to demarcate the iris' inner and outer boundaries. Next, they use LHT to demarcate both upper and lower eyelids [11]. To remove eyelashes, they adapted a simple thresholding method, i.e., if the length of eyelashes is found lower than a specific threshold value, then it is considered as an eyelash region otherwise non-eyelash. This scheme is validated on the UBIRIS V2.0 [43] (Table 4), refer to full text article for temporal and accuracy details. Fig. 28 shows its iris localization results.

In 2014, Jan *et al.* [4], published: *Iris segmentation for visible wavelength and near infrared eye images.* To suppress reflections, authors use a scheme published in [3]. After that, this algorithm marks a set of the Seed-pixels in the preprocessed eyeimage adaptively. Next, it uses a two-fold strategy based on the Circu-differential accumulator (CDA) and the image gray-level statistics to localize the coarse iris location robustly. The proposed CDA has close resemblance with CHT, but it demands for relatively less memory and is free from the thresholding parameters as well. After that, it localizes circular pupillary boundary in a similar scheme, which is then verified via an intensity test as well. Then, it extracts a refine estimate for limbic boundary. In addition, it uses a combination of the Fourier series and radial gradients to regularize iris contours. Finally, it localizes eyelids through a Para-differential accumulator (PDA). Moreover, the eyelashes and reflections are localized adaptively in the polar form of iris. This scheme is validated on MMU V2.0 [29], CASIA-

Iris-Lamp [28], and UBIRIS V1.0 [43], which resulted in the following recognition accuracy: $EER = 0.028$, $EER = 0.020$, and $EER = 0.008$, respectively (Table 4). Similarly, on the average (*MATLAB V7.1, Intel CORETM i5-2430M, CPU speed: 2.4GHz and 2GB RAM*), it takes 0.84, 0.97, and 0.68Sec, respectively, on the mentioned databases. Fig. 29(a) shows some accurate iris localization results. Similarly, Fig. 29(b) & (c) represents a polar iris image and its corresponding noise-mask where eyelids, reflections, and eyelashes are also marked, respectively.

In 2015, Raffei *et al.* [62] published: *A low lighting or contrast ratio visible iris recognition using iso-contrast limited adaptive histogram equalization*. Eyeimage conditions such as the low lighting or low contrast between iris and pupil are one of the challenges for the iris recognition systems in the non-cooperative environment and under VW illumination. To resolve this issue, authors used the iso-contrast limited adaptive histogram equalization. First, they partitioned eyeimage into the contextual sub-region. Next, the stated scheme transfers pixel-intensity by referring to a local intensity histogram and a newly suggested cumulative distribution function. After enhancing eyeimage, they localize iris contours via CHT, eyelids via LHT, and eyelashes via a thresholding scheme. This scheme is validated on UBIRIS V2.0 [43], see full text for other details. Fig. 30 illustrates some iris localization results of this method.

In 2015, Hu *et al.* [8] published: *Improving colour iris segmentation using a model selection technique*. In this article, authors proposed a new scheme to improve the reliability and accuracy of iris segmentation in the color eyeimages, i.e., in particular for the eyeimages captured with the static and mobile devices. This scheme is a fusion strategy based on a selection amongst the segmentation outcomes of different segmentation methods/models. To begin with, authors first present and analyze an iris segmentation framework. It uses three

different models to demonstrate that improvements can be achieved by selecting among the outcomes generated by three models. Then, they incorporate a model selection method that defines the optimal segmentation based on a ring-shaped region around outer segmentation boundary identified by each model. Authors adapted the histogram of oriented gradients (HOG) as the features extracted from ring-shaped region and then train a SVM (support vector machine)-based classifier, which offers the selection decision. This scheme is validated on MICHE dataset [63], UBIRIS V2.0 [43], and FRGC dataset (a face-data set) [64]. Fig. 31(a) & (b) illustrates some false and accurate iris segmentation results of this scheme, respectively.

In 2015, Umer *et al.* [65] published: *Iris recognition using multiscale morphologic features*. The scheme comprises image pre-processing, feature extraction, and classification. During pre-processing, authors localize the iris inner and outer contours using the Restricted Circular Hough transformation (RCHT). Herein, no scheme is offered for removing noise, eyelids, eyelashes, and reflections. As indicated in Table 5, on the average (*MATLAB on fedora O/S of version 14.0, Intel Core i3 processor*), it takes 0.89, 0.41, 0.65, and 0.92Sec for iris localization on the UPOL V1.0 [66], MMU V1.0 [29], IITD V1.0 [53], and UBIRIS V1.0 [43], respectively. Besides, authors computed both verification and identification performance of this article on the stated databases. On the average, it achieved EER = 0.008, EER = 0.009, EER = 0.015, and EER = 0.011 for the stated databases, respectively. Fig. 32 illustrates some iris localization results of this scheme.

In 2015, Haindl and Krupicka [67] published: *Unsupervised detection of non-iris occlusions*. In this article, authors first suppress reflections in the blue spectral component of the input RGB eyeimage using the inpainting algorithm. Next, they localize the accurate eye region through a two-step scheme; where a rough estimate of iris location is first found using

generalized Hough transform (GHT) on a sub-sampled preprocessed image and then the refine iris contours are marked using the modified IDO in the red spectral component. Authors also validate the actual iris location through an intensity test. Then, they transform the localized annular (Cartesian form) iris region into rectangular form (Polar form). To avoid eyeimages containing no eye at all, they detect a missing iris (e.g., input image containing closed eye) in resultant polar image through a thresholding scheme in the GHT space. Finally, eyelids and reflections are detected in the red and blue spectral components of polar image, respectively. This scheme is validated on UBIRIS V2.0 [43]. Fig. 33 illustrates some iris segmentation results of this scheme.

In 2015, Barra *et al.* [9] published: *Ubiquitous iris recognition by means of mobile devices*. In this article, authors propose a comprehensive scheme based on the spatial histograms for iris authentication on the cellular phones. In this article, authors localize iris contours using the histogram based strategy involving homogeneity and separability concepts. This scheme is validated on UBIRIS V2.0 [43], UPOL V1.0 [66], and MICHE-I [63] iris datasets.

In 2016, Frucci *et al.* [68] published: *WIRE: Watershed based iris recognition*. In this article, iris is segmented as follows. First, authors rectify color/illumination of input RGB eyeimage, decimate it, and filter it with a median filter to calm down the effects of rapid gray-level variations and artifacts if any. Next, they detect iris outer boundary using a combination of the Watershed transform, image binarization, circle fitting, and limbic boundary refinement. Following that, they localize pupillary boundary via a hybrid of the Canny filtering and circle fitting schemes. This algorithm isolates eyelids in the valid iris part. It is validated on UBIRIS V2.0 [43]. Fig. 34 illustrates some iris segmentation results for this scheme.

4. Conclusion

To conclude, this study provides a recent survey of the iris segmentation and localization schemes published following 2010, for the non-ideal iris biometric systems. In addition to a short iris biometric history and motivation, it exposes readers to the basics of the ideal versus non-ideal iris biometric systems. For ideal systems, it explicitly details the two pioneered iris recognition algorithms developed by Daugman and Wildes. For non-ideal systems, it details the less-constrained and un-constrained iris biometric systems. Finally, it presents a comprehensive survey of state of the art in iris segmentation/localization in less-constrained and un-constrained iris biometric systems. The main objective of this survey is not to compare the research work of different publications, but to serve readers as a quick reference for recent development in the non-ideal iris biometric systems. However, the readers are recommended to consult the corresponding publications for more details if interested in. Literature reveals some valuable survey publications on the subject topic, but their scope is kept limited until 2010. For this purpose, this survey encompasses prominent publications following 2010, for both NIR and VW image data. No doubt, this study would surely be a valuable contribution towards the relevant iris biometric research community. It is because that most of the researchers (especially naïve) often prefer consulting survey articles while starting research in a new paradigm.

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Fig. 1: A color eyeimage showing eyeparts

Fig. 2: A typical (Daugman type) iris biometric system.

(a)

(b)

(c)

(d)

Fig. 3: (a) & (b) Ideal eyeimage acquisition setup and a typical ideal iris biometric system, respectively. (c) & (d) Typical NIR eyeimages [28, 29].

Fig. 4: Iris normalization using rubber sheet model.

Fig. 5: (a) & (b) IrisCode and its corresponding noise mask, respectively.

Fig. 6: Wildes' image acquisition setup.

Fig. 7: (a)-(d) $I(x, y)$ and $E(x, y)$ extracted by biasing ∇ in both the vertical and horizontal, vertical, and horizontal directions, respectively.

Fig. 8: (a) 2D view of H_c , for a particular radius. (b) Iris localized with Wildes' approach.

(a)

(b)

Fig. 9: (a) & (b) Typical non-ideal iris biometric systems.

Fig. 10: (a) & (b) Non-ideal eyeimages acquired with NIR and VW illumination, respectively.

Fig. 11: Iris segmentation results of the stated algorithm.

Fig. 12: Segmentation results of the mentioned algorithm.

Fig. 13: True iris segmentation results, on the stated iris databases.

Fig. 14: Iris segmentation; original eyeimage, pupil localization, and complete iris localization, respectively.

Fig. 15: Iris segmentation results, for IUPUI remote iris database.

Fig. 16: (a) & (b) Accurate and false iris segmentation, respectively.

Fig. 17: Iris segmentation results, for the UBIRIS V1.0.

Fig. 18: (a) & (b) Some accurate and false iris localization, respectively.

Fig. 19: True iris segmentation results, for some of the images taken from the stated iris databases.

Fig. 20: Iris localization results of the stated algorithm on the stated iris databases.

Fig. 21: (a) & (b) Some accurate and false iris localization results, respectively.

Fig. 22: Iris segmentation results of the mentioned scheme on the colored version of the UBIRIS V1.0.

Fig. 23: (a) Some accurate iris localization results. (b) & (c) Polar iris image and its corresponding noise-mask, respectively.

Fig. 24: Iris segmentation results, for images taken from UBIRIS V1.0.

Fig. 25: (a) & (b) Some accurate and false iris localization results, respectively.

Fig. 26: (a) & (b) Some accurate and false pupil localization, respectively.

Fig. 27: (a) & (b) Some accurate and false iris localization respectively.

Fig. 28: Upper and lower rows illustrate color eyeimages with reflections and with reflections suppressed, respectively.

Fig. 29: (a) Some accurate iris localization results. (b) & (c) Polar iris image and its corresponding noise-mask, respectively.

Fig. 30: Iris localization results, for the UBIRS V2.0.

Fig. 31: (a) & (b) Some false and accurate iris segmentation results, respectively.

Fig. 32: Accurate iris localization results.

Fig. 33: Iris segmentation results, for the UBIRIS V2.0.

Fig. 34: True iris segmentation results on the UBIRIS V2.0.

Table 1
Contemporary iris segmentation and localization schemes for non-ideal iris biometric systems

Method	Main iris segmentation or localization techniques or operators used	Evaluation metric	Accuracy (%)	Average segmentation time	Used Databases
Chen <i>et al.</i> [41]	Merged active contour model	Hamming distance as a metric for recognition	EER = 0.43	38ms	THUIris V1.0, CASIA-IrisV3-Lamp, and ICE V1.0
R.M. Farouk [42]	CHT, LHT, and region based active contours	Hamming distance as a metric for recognition	97.17 95.8 ^a	--	a: results obtained on UBIRIS V1.0 and CAISA-IrisV3-Interval, respectively.
Roy <i>et al.</i> [44]	Direct Least Square (DLS)-based elliptical fitting ; Geometric shape prior with local and global information	Hausdorff Distance (HD) as a metric for recognition	98.30, 97.21, 97.49, and 95.68 ^a	804ms	a: results obtained on ICE 2005, CASIA-IrisV3-Interval, UBIRIS V1.0, and WVU V1.0 respectively.
Roy <i>et al.</i> [48]	DLS-based elliptical fitting; DLS-based elliptical fitting;	Adaptive asymmetrical support vector machines (SVM)	98.21, 96.32, and 97.51 ^a	810ms	a: results obtained on ICE 2005, WVU V1.0, and UBIRIS V2.0, respectively.
Yingzi <i>et al.</i> [49]	DLS-based elliptical fitting	Recognition accuracy; Objective metric used to compute segmentation accuracy.	EER = 0.0179 ^a ; EER = 0.0295 ^b ; 890.08 ^c ;	--	IUPUI remote iris database; a : Recognition accuracy using 2DGabor filter b : Recognition accuracy using 1DGabor filter c : Iris segmentation accuracy, with standard deviation 6.52%.
Puhan <i>et al.</i> [51]	Thresholding based techniques supplemented with Euclidean distance.	Objective metric used for computing iris segmentation accuracy.	98.49 and 98.75 ^a ; 94.47 and 87.17 ^b .	15ms	a: Limbic boundary segmentation accuracy on session-1 and session-2 of UBIRIS V1.0, respectively; b : Pupillary boundary segmentation accuracy on session-1 and session-2 of UBIRIS V1.0, respectively;

Note: For explicit details, refer to full text article.

Table 2
Contemporary iris segmentation and localization schemes for non-ideal iris biometric systems

Method	Main iris segmentation or localization techniques or operators used	Evaluation metric	Accuracy (%)	Average segmentation time	Used Databases
Radman <i>et al.</i> [52]	Circular Gabor filter; Modified CHT and IDO;	--	99.67 ^a 99.35 ^b ; 99.42 ^c 98.53 ^d	--	a & b: Results obtained on the Session-1 and 2 of the UBIRIS V1.0, with modified IDO, respectively. c & d: Results obtained on the Session-1 and 2 of the UBIRIS V1.0, with modified IDO, respectively.
Jan <i>et al.</i> [3]	Hybrid of CHT, gray-level statistics, 2D object's geometry, and adaptive thresholding.	Subjective observation	100, 99.90, 100, 99.5, 97, 98, 99.5, 100, and 93.5 ^a .	2.67, 2.70, 7.20, 7.75, 3.91, 6.40, 4.93, 5.61, 1.14, and 8.52Sec ^a .	a : Results obtained on the MMU V1.0, MMU (new) V2.0, CASIA-IrisV1, CASIA-IrisV3-Interval, CASIA-IrisV3-Twins, CASIA-IrisV3-Lamp, CASIA-IrisV3-Thousand, CASIA-IrisV4-Syn, UBIRIS V1.0, and IITD V1.0, respectively
Mahlouji and Noruzi [54]	CHT and LHT	Hamming distance	98.13, 99.73, and 99.18 ^a ; 98, 98.63, and 97.63 ^b ; 98, 98.63, and 97.63 ^c .	--	a, b, and c : Recognition accuracy for pupillary, limbic, and eyelids on CASIA-IrisV1, CASIA-IrisV3-Interval, and BATH V1.0, respectively.
Mehrotra <i>et al.</i> [56]	Thresholding based scheme	--	99.02, 99.55, and 96.59 ^a	0.3383, 0.3960, and 0.2820 Sec ^a	a: Results obtained on BATH V1.0, CASIA-IrisV3-Interval, and UBIRIS V1.0, respectively

Note: For explicit details, refer to full text article.

Table 3

Contemporary iris segmentation and localization schemes for non-ideal iris biometric systems

Method	Main iris segmentation or localization techniques or operators used	Evaluation metric	Accuracy (%)	Average segmentation time	Used Databases
Jan <i>et al.</i> [7]	A combination of CHT, 2D object geometry, image gray-level statistics, and thresholding based schemes	Subjective	100, 99.21, 99.23, 99.23, 100, and 99.12 ^a	3.0, 3.35, 3.4, 3.6 1.2, and 1.4Sec ^a	a : Results obtained on CASIA-IrisV1, CASIA-IrisV3-Lamp, CASIA-IrisV4-Thousand, IITD V1.0, MMU V1.0, and MMU V2.0, respectively.
Sahmoud and Abuhaiba [57]	K-means clustering algorithms, CHT, and LHT Otsu's thresholding, Euclidean distance transform, circular pixel counting scheme (CPCS); parabolic pixel counting scheme (PPCS), and thresholding based schemes	Hamming distance	98.76	1.49Sec	UBIRIS V1.0
Jan <i>et al.</i> [2]		Hamming distance	99.6 and 99.4 ^a	0.8 and 0.5Sec ^a	a : Results obtained on UBIRIS V1.0 and CASIA-IrisV3-Interval, respectively
Radman <i>et al.</i> [58]	Circular Gabor filter; Fast IDO; and live wire scheme	Subjective	97.36 and 96.88 ^a	1.09Sec	a : Results obtained on the Session 1 & 2 of UBIRIS V1, respectively.
Jan <i>et al.</i> [59]	CHT, adaptive thresholding, 2D object properties, Radial gradient operator, and Fourier series.	Subjective	100, 99.2, 99.4, 99.25, and 99.3 ^a	0.60, 0.80, 1.23, 1.33, and 1.42Sec ^a	a : Results obtained on the MMU V1.0, MMU (new) V2.0, CASIA-IrisV3-Interval, CASIA-IrisV3-Lamp, and CASIA-IrisV4-Thousand, respectively

Note: For explicit details, refer to full text article.

Table 4
Contemporary iris segmentation and localization schemes for non-ideal iris biometric systems

Method	Main iris segmentation or localization techniques or operators used	Evaluation metric	Accuracy (%)	Average segmentation time	Used Databases
Saad <i>et al.</i> [60]	Thresholding, Seed-fill algorithm, and the circle fitting algorithm	Subjective	100	0sec approximately	CASIA-IrisV3-interval
Jan <i>et al.</i> [1]	Multi-valued adaptive threshold, 2D object properties, IDO, and Fourier series	Quantitatively	100, 99.05, 99.46, and 99.55 ^a	1.5Sec	a : results obtained on CASA-IrisV1, CASIA-IrisV3-Lamp, IITD V1.0, and MMU V1.0, respectively
Raffei <i>et al.</i> [61]	LIPSVM method based on a line intensity profile; CHT, LHT, and thresholding	Hamming distance	see [61]	see [61]	UBIRIS V2.0
Jan <i>et al.</i> [4]	Circu-differential accumulator (CDA); Para-differential accumulator; and Fourier series	Hamming distance	EER = 0.028, EER = 0.020, and EER = 0.008 ^a	0.84, 0.97, and 0.68Sec ^a	a : results obtained on MMU V2.0, CASIA-Iris-Lamp, and UBIRIS V1.0, respectively

Note: For explicit details, refer to full text article.

Table 5
Contemporary iris segmentation and localization schemes for non-ideal iris biometric systems

Method	Main used iris segmentation or localization techniques or operators	Evaluation metric	Accuracy (%)	Average segmentation time	Used Databases
Raffei <i>et al.</i> [62]	Combination of local intensity histogram, cumulative distribution functions, CHT, LHT, and thresholding fusion strategy based on a selection amongst the segmentation outcomes of different segmentation methods/models	Refer to [62]	Refer to [62]	Refer to [62]	UBIRIS V2.0
Hu <i>et al.</i> [8]		Refer to [8]	Refer to [8]	Refer to [8]	MICHE dataset, UBIRIS V2.0, and FRGC dataset
Umer <i>et al.</i> [65]	Restricted Circular Hough transformation (RCHT)	SVM classifier using intra and inter-class difference vectors.	EER = 0.008, EER = 0.009, EER = 0.015, and EER = 0.011 ^a	0.89, 0.41, 0.65, and 0.92 Sec ^a	a : Results obtained on UPOL V1.0, MMU V1.0, IITD V1.0, and UBIRIS V1.0, respectively

Note: For explicit details, refer to full text article.